

Investment Case 2

(Based on Python, Risk = Standard Variance(Yearly))

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1. The risk of these three assets show as followings:

Risk		
TMI	TKA	OLE
0.156294445	0.391078229	0.484089827

2. The risk resources of two companies are summarized in the following table:

Risk Resources	
ThyssenKrupp AG	Recent currency moves suggest some (material) risk of the potential for a demand shock
Deoleo SA	Raw material(weather)
	Competitive conditions(the industry has seen large entry and exit in the last decade)
	Demand in Spain and Italy is very price elastic
	The leverage of the new strategy is high
	Deoleo's banks may want to sell the equity stakes they acquired in the 2010 reorganization

3. Based on question 1, I predict that the 4th portfolio is riskier than any other one because the risk of OLE is the largest among all these four assets. However, when I calculate the risk of each portfolio, surprising to find that the risk of the 3rd portfolio is the biggest, which is different from my prediction. (Exhibit 1)

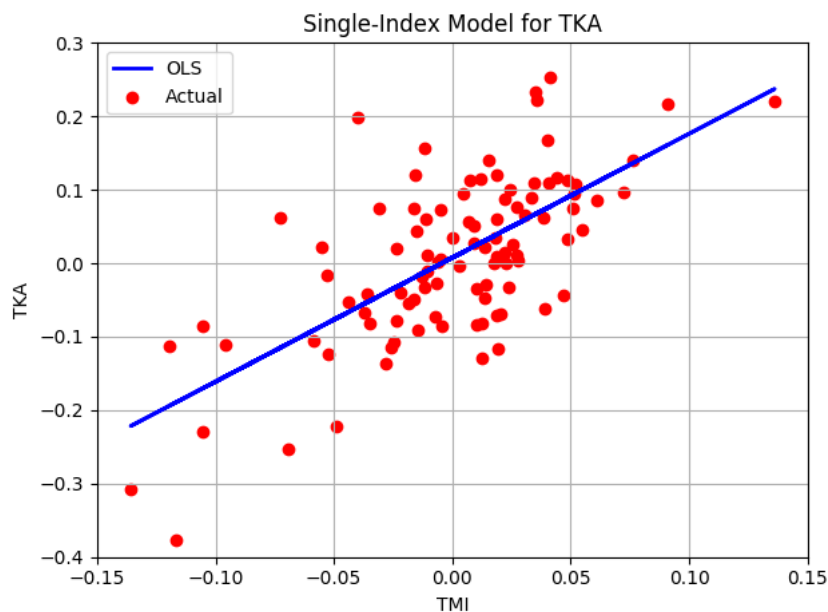
Risk			
Portfolio1	Portfolio2	Portfolio3	Portfolio4
0.101289363	0.109145308	0.115549591	0.109868009

As for reasons, I think it is because of the **correlations** of the four assets.
Therefore, I calculate the correlations between them, showing as followings:

Correlation	Bond	TMI	TKA	OLE
Bond	1	-0.205479221	-0.005322952	0.054261466
TMI	-0.205479221	1	0.679991853	0.246788084
TKA	-0.005322952	0.679991853	1	0.260611932
OLE	0.054261466	0.246788084	0.260611932	1

Through the table, we can easily find that the **correlation** between TMI and TKA is very **high** (0.679991853), which means the assets are not totally diversified and risk has not been eliminate because of it.

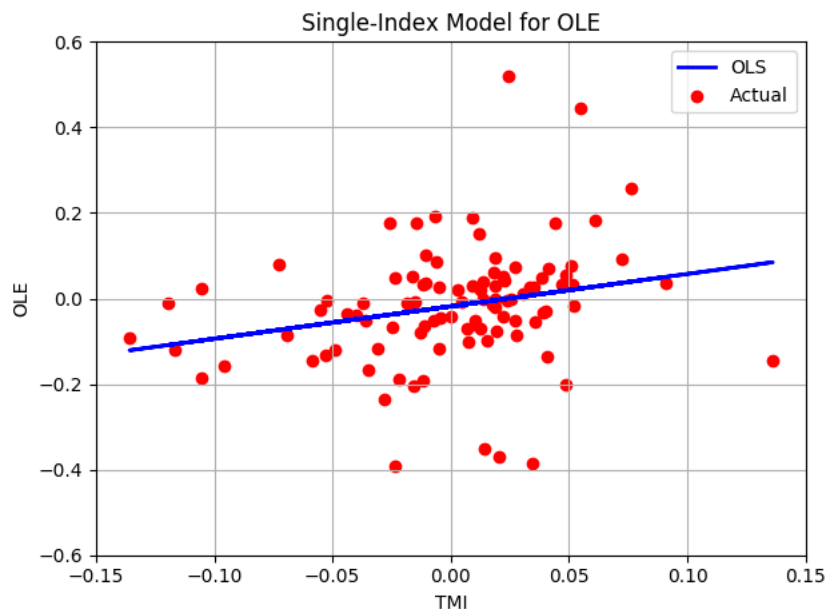
4. The regression plot for excess return of **TKA(Y)** and **TMI(X)** shows as following:



The regression summary for excess return of TKA(Y) and TMI(X) shows as following:

OLS Regression Results						
Dep. Variable:	TKA	R-squared:	0.460			
Model:	OLS	Adj. R-squared:	0.455			
Method:	Least Squares	F-statistic:	82.76			
Date:	Wed, 14 Nov 2018	Prob (F-statistic):	1.19e-14			
Time:	23:41:34	Log-Likelihood:	106.50			
No. Observations:	99	AIC:	-209.0			
Df Residuals:	97	BIC:	-203.8			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0076	0.008	0.902	0.369	-0.009	0.024
TMI	1.6877	0.186	9.097	0.000	1.320	2.056
Omnibus:	2.786		Durbin-Watson:	1.793		
Prob(Omnibus):	0.248		Jarque-Bera (JB):	2.188		
Skew:	0.337		Prob(JB):	0.335		
Kurtosis:	3.274		Cond. No.	22.1		

The regression plot for excess return of OLE(Y) and TMI(X) shows as following:



The regression summary for excess return of **OLE(Y)** and **TMI(X)** shows as following:

OLS Regression Results						
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Dep. Variable:	OLE	R-squared:	0.061			
Model:	OLS	Adj. R-squared:	0.051			
Method:	Least Squares	F-statistic:	6.247			
Date:	Wed, 14 Nov 2018	Prob (F-statistic):	0.0141			
Time:	23:50:10	Log-Likelihood:	57.987			
No. Observations:	99	AIC:	-112.0			
Df Residuals:	97	BIC:	-106.8			
Df Model:	1					
Covariance Type:	nonrobust					
<hr/>						
	coef	std err	t	P> t	[0.025	0.975]
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const	-0.0183	0.014	-1.338	0.184	-0.045	0.009
TMI	0.7569	0.303	2.499	0.014	0.156	1.358
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Omnibus:	12.884	Durbin-Watson:	2.244			
Prob(Omnibus):	0.002	Jarque-Bera (JB):	40.358			
Skew:	0.150	Prob(JB):	1.72e-09			
Kurtosis:	6.113	Cond. No.	22.1			
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Therefore, the table of **alpha**, **beta**, **R²**, **total risk**, **systematic risk** and **non-systematic risk** of **TKA** and **OLE** shows as followings:

	Alpha	Beta	R-squared	Total Risk	Systematic Risk	Non-systematic Risk
TKA	0.007557	1.687714	0.460	0.391125609	0.265386998	0.287313389
OLE	-0.018298	0.756943	0.061	0.483873187	0.119026649	0.469005243

- After building the single-factor model for **TKA** and **OLE**, I find the result match the brief summary of risk resources in **Problem 2**.

Firstly, considering **TKA**, I find the **Beta** (1.687714) is pretty **high**, which means it is sensitive to the market, and it can explain the huge recession of this stock along with the market index. Furthermore, the **Alpha** (0.007557) of TKA is pretty **low**, which helps to explain why its tendency of return was predicted accurately in the past few years. Also, the **Systematic Risk** (0.265386998) can explain this result, for it grows as auto and steal section develops. In **Problem 2**, I summarized that the main risk of this firm is from the material risk for a demand shock, and we can see it seems significant due to the value of **Non-systematic Risk** (0.287313389), which is larger than **Systematic Risk** (0.265386998).

Secondly, as for **OLE**, given the products of this company are ordinary consumptions in daily life, the risk of this firm will be lower than many of other firms in the market and of course, the **Beta** (0.756943) is **lower** than the average of the whole market as well. And the **low Beta** can explain why the price of the stock is pretty still while most others are falling extremely in the crisis. Then we can take a view of **Non-systematic Risk** (0.469005243), which is high. It is because of the great competition, the high leverage of the strategy, the high elastic of demand and some other reasons that cannot be explained by the market index.

6. Based on **Problem 4**, we can explain the **Problem 2** more specifically, we were surprised to find that the risk of portfolio 4 is lower than portfolio 2. However, we can find the **Beta** of TKA (1.687714) is much larger than this of OLE (0.756943), which means the correlation of TKA and market is larger than this of OLE and market. Also, we can see that the **Non-systematic Risk** of TKA (0.082940) is lower than this of OLE (0.135390). Therefore, the total risk of portfolio 3 are supposed to be **higher** than portfolio 4.
7. Because of the small portion of assets except bonds and market index, I predict the **Beta** will be close to the portion of TMI, which means the **Benchmark** is 0.6, **Portfolio 1** is 0.65, **Portfolio 2** is 0.7 , **Portfolio 3** is a little **larger than 0.65** and **Portfolio 4** is a little **larger than 0.65** but **less than Portfolio 3**.

Then I use OLS to analyze such 5 portfolios, and the results are as following (**The OLS report are in the Appendix Exhibit 2**):

	Alpha	Beta	R-squared	Total Risk	Systematic Risk	Non-systematic Risk
Benchmark	-1.08E-19	0.6	1	0.094347851	0.094347851	3.73067E-17
Portfolio1	-8.13E-20	0.650	1	0.102210172	0.102210172	2.01615E-17
Portfolio2	-1.08E-18	0.700	1	0.110072493	0.110072493	3.48736E-17
Portfolio3	3.78E-04	0.734385705	0.985	0.116369638	0.115479522	0.014365669
Portfolio4	-9.15E-04	0.687847173	0.955	0.110674414	0.108161505	0.023450262

Then the functions are showing as followings:

- $r_{benchmark} = -1.08 * 10^{-19} + 0.6 * r_{TMI} + \epsilon$
- $r_{portfolio1} = -8.13 * 10^{-20} + 0.65 * r_{TMI} + \epsilon$
- $r_{portfolio2} = -1.08 * 10^{-18} + 0.7 * r_{TMI} + \epsilon$
- $r_{portfolio3} = 3.78 * 10^{-4} + 0.734385705 * r_{TMI} + \epsilon$
- $r_{portfolio4} = -9.15 * 10^{-4} + 0.687847173 * r_{TMI} + \epsilon$

8. The Alpha of portfolio 3 is positive, but not really significantly, which means the real return of portfolio 3 is higher than its expected return, it means we can earn some extra money beyond the portion connected to excess return of market index. Take **Systematic Risk** (0.115479522) and **Non-systematic Risk** (0.014365669) into consideration, we can find that the systematic risk contributes to the most of the risk, therefore, alpha may come from the fast development of steel and auto section, which is because of the policy of the country.

However, we can also find most alphas are not noticeable positive, which means most of the excess returns of these portfolios can be explained by the growing or depression of the financial market.

9. After removing the data in 2008, I use OLS to analyze such 5 portfolios, and the results are as following (The OLS report are in the Appendix Exhibit 3):

	Alpha	Beta	R-squared	Total Risk	Systematic Risk	Non-systematic Risk
Benchmark	-4.87E-18	0.6	1	0.0798096	0.0798096	1.71122E-17
Portfolio1	-6.02E-18	0.650	1	0.0864604	0.0864604	2.88971E-17
Portfolio2	-6.22E-18	0.700	1	0.0931112	0.0931112	3.42781E-17
Portfolio3	7.84E-05	0.739686216	0.984	0.099220513	0.098390101	0.012810076
Portfolio4	-1.32E-03	0.705617593	0.937	0.097002054	0.093858429	0.024494769

Then the functions are showing as followings:

- $r_{benchmark} = -4.87 * 10^{-18} + 0.6 * r_{TMI} + \epsilon$
- $r_{portfolio1} = -6.02 * 10^{-18} + 0.65 * r_{TMI} + \epsilon$
- $r_{portfolio2} = -6.22 * 10^{-18} + 0.70 * r_{TMI} + \epsilon$
- $r_{portfolio3} = 7.84 * 10^{-5} + 0.739686216 * r_{TMI} + \epsilon$
- $r_{portfolio4} = -1.32 * 10^{-3} + 0.705617593 * r_{TMI} + \epsilon$

Compare the results with Problem 7, we can easily find the portfolio 1~3 nearly have no changes, however the Non-Systematic risk of Portfolio 3 decreases (0.012810076), and 4 increases (0.024494769), which reflects that TKA is more comprehensible by the market than OLE, especially when the Crisis happened and the market index decreased violently. Plus, we can see the Beta of Portfolio 4 increases (from 0.687847173 to 0.705617593), it can be explained by the Crisis when necessities stay still while the market index decreased considerable. Therefore, when we take apart the data of this period, its trend can be explained by the financial market more comprehensive.

Also, we can find the general performances of these portfolios by taking apart the data in 2008 when the Crisis happened. And from this point of view, we can draw a conclusion that Portfolio 3 can earn a little more money beyond the market tendency while others have negative alphas. Furthermore, the Portfolio 3 is more closely connected to market than any other assets because of the highest Beta (0.739686216). Last but not least, The Portfolio 4 can distribute more risk because its Non-systematic Risk (0.024494769) has the biggest part of contribution of Total risk (0.097002054) among all portfolios.

Appendix

Exhibit 1: Return of Different Portfolios

Date	Bond	TMI	TKA	OLE	Portfolio1	Portfolio2	Portfolio3	Portfolio4
31/1/2006	0.20%	3.72%	23.56%	3.00%	2.49%	2.66%	3.66%	2.63%
28/2/2006	0.21%	2.09%	1.14%	-1.68%	1.43%	1.53%	1.48%	1.34%
31/3/2006	0.21%	2.09%	12.21%	3.23%	1.43%	1.53%	2.03%	1.58%
28/4/2006	0.21%	0.67%	9.74%	-0.43%	0.51%	0.53%	0.99%	0.48%
31/5/2006	0.23%	-5.29%	2.34%	-2.36%	-3.36%	-3.63%	-3.25%	-3.49%
30/6/2006	0.23%	0.53%	-0.15%	2.42%	0.43%	0.44%	0.41%	0.53%
31/7/2006	0.24%	1.61%	2.36%	4.27%	1.13%	1.20%	1.24%	1.33%
31/8/2006	0.25%	2.63%	-2.93%	-0.17%	1.80%	1.92%	1.64%	1.78%
29/9/2006	0.26%	2.00%	0.23%	-1.18%	1.39%	1.48%	1.39%	1.32%
31/10/2006	0.27%	3.59%	9.21%	2.89%	2.43%	2.59%	2.88%	2.56%
30/11/2006	0.28%	-0.34%	0.52%	8.76%	-0.12%	-0.15%	-0.11%	0.30%
29/12/2006	0.28%	3.85%	22.44%	-5.02%	2.60%	2.78%	3.71%	2.34%
31/1/2007	0.30%	2.11%	3.85%	6.40%	1.48%	1.57%	1.65%	1.78%
28/2/2007	0.30%	-2.04%	2.36%	5.26%	-1.22%	-1.34%	-1.12%	-0.97%
30/3/2007	0.30%	2.59%	0.30%	4.64%	1.79%	1.90%	1.79%	2.01%
30/4/2007	0.31%	3.36%	6.86%	1.30%	2.29%	2.44%	2.62%	2.34%
31/5/2007	0.32%	2.52%	9.15%	-3.91%	1.75%	1.86%	2.19%	1.54%
29/6/2007	0.32%	-0.76%	1.51%	4.00%	-0.38%	-0.44%	-0.32%	-0.20%
31/7/2007	0.33%	-3.36%	-6.39%	-0.62%	-2.07%	-2.25%	-2.40%	-2.12%
31/8/2007	0.32%	-1.21%	4.75%	-0.48%	-0.67%	-0.75%	-0.45%	-0.71%
28/9/2007	0.31%	0.30%	3.84%	-3.89%	0.30%	0.30%	0.48%	0.09%
31/10/2007	0.32%	2.87%	2.91%	0.14%	1.98%	2.11%	2.11%	1.97%
30/11/2007	0.31%	-4.95%	-11.99%	0.00%	-3.11%	-3.37%	-3.72%	-3.12%
31/12/2007	0.31%	-1.55%	-5.12%	-0.71%	-0.90%	-0.99%	-1.17%	-0.95%
31/1/2008	0.31%	-11.66%	-11.01%	-0.71%	-7.47%	-8.07%	-8.04%	-7.52%
29/2/2008	0.31%	-0.87%	15.96%	3.60%	-0.46%	-0.52%	0.33%	-0.29%

31/3/2008	0.30%	-4.06%	-4.90%	-3.19%	-2.53%	-2.75%	-2.79%	-2.71%
30/4/2008	0.31%	5.50%	11.11%	-1.51%	3.68%	3.94%	4.22%	3.59%
31/5/2008	0.32%	-0.18%	7.62%	3.06%	-0.01%	-0.03%	0.36%	0.13%
30/6/2008	0.35%	-10.17%	-8.14%	2.80%	-6.49%	-7.01%	-6.91%	-6.37%
31/7/2008	0.34%	-2.13%	-10.32%	-6.41%	-1.27%	-1.39%	-1.80%	-1.60%
31/8/2008	0.34%	1.68%	-4.45%	0.15%	1.21%	1.28%	0.97%	1.20%
30/9/2008	0.27%	-11.40%	-37.38%	-11.76%	-7.32%	-7.90%	-9.20%	-7.92%
31/10/2008	0.16%	-13.42%	-30.54%	-9.00%	-8.67%	-9.35%	-10.20%	-9.13%
30/11/2008	0.15%	-7.10%	6.40%	8.06%	-4.56%	-4.92%	-4.25%	-4.17%
31/12/2008	0.11%	-3.86%	20.00%	-3.65%	-2.47%	-2.67%	-1.48%	-2.66%
31/1/2009	0.09%	-3.37%	-8.16%	-16.45%	-2.16%	-2.33%	-2.57%	-2.99%
28/2/2009	0.07%	-9.49%	-11.09%	-15.79%	-6.14%	-6.62%	-6.70%	-6.94%
31/3/2009	0.05%	2.10%	-6.80%	-36.87%	1.38%	1.49%	1.04%	-0.46%
30/4/2009	0.06%	13.68%	22.03%	-14.45%	8.91%	9.59%	10.01%	8.19%
31/5/2009	0.06%	4.11%	11.09%	-13.66%	2.69%	2.90%	3.24%	2.01%
30/6/2009	0.05%	-1.23%	-1.78%	-7.77%	-0.78%	-0.85%	-0.87%	-1.17%
31/7/2009	0.04%	9.15%	21.74%	3.78%	5.96%	6.42%	7.05%	6.15%
31/8/2009	0.03%	5.16%	9.46%	3.36%	3.36%	3.62%	3.84%	3.53%
30/9/2009	0.04%	2.82%	0.38%	-8.54%	1.85%	1.99%	1.86%	1.42%
31/10/2009	0.04%	-2.29%	-7.77%	-39.11%	-1.47%	-1.59%	-1.87%	-3.43%
30/11/2009	0.04%	0.81%	11.26%	-9.98%	0.54%	0.58%	1.10%	0.04%
31/12/2009	0.03%	6.14%	8.60%	18.38%	4.00%	4.31%	4.43%	4.92%
31/1/2010	0.03%	-2.58%	-11.42%	17.81%	-1.67%	-1.80%	-2.24%	-0.78%
28/2/2010	0.02%	-0.50%	0.52%	-11.82%	-0.32%	-0.34%	-0.29%	-0.91%
31/3/2010	0.03%	7.28%	9.62%	9.23%	4.74%	5.11%	5.22%	5.20%
30/4/2010	0.03%	-1.13%	-3.32%	-19.11%	-0.72%	-0.78%	-0.89%	-1.68%
31/5/2010	0.02%	-5.86%	-10.62%	-14.43%	-3.80%	-4.10%	-4.33%	-4.52%
30/6/2010	0.02%	-0.70%	-7.20%	-5.24%	-0.45%	-0.48%	-0.81%	-0.71%
31/7/2010	0.03%	4.92%	11.34%	5.53%	3.21%	3.45%	3.77%	3.48%
31/8/2010	0.03%	-1.58%	-4.84%	-1.75%	-1.02%	-1.10%	-1.26%	-1.11%

30/9/2010	0.04%	3.49%	10.95%	-38.46%	2.28%	2.46%	2.83%	0.36%
31/10/2010	0.06%	2.51%	10.04%	51.93%	1.65%	1.77%	2.15%	4.25%
30/11/2010	0.05%	-1.52%	12.17%	-20.26%	-0.97%	-1.05%	-0.36%	-1.99%
31/12/2010	0.04%	5.52%	4.58%	44.44%	3.60%	3.88%	3.83%	5.82%
31/1/2011	0.06%	1.47%	-2.86%	-35.10%	0.98%	1.05%	0.83%	-0.78%
28/2/2011	0.06%	2.26%	1.48%	5.19%	1.49%	1.60%	1.56%	1.75%
31/3/2011	0.08%	-3.54%	-4.05%	-4.93%	-2.27%	-2.45%	-2.48%	-2.52%
30/4/2011	0.09%	2.80%	7.71%	-5.19%	1.85%	1.99%	2.23%	1.59%
31/5/2011	0.09%	-1.01%	6.05%	-6.25%	-0.62%	-0.68%	-0.33%	-0.94%
30/6/2011	0.10%	-3.01%	7.54%	-11.67%	-1.92%	-2.08%	-1.55%	-2.51%
31/7/2011	0.08%	-2.75%	-13.65%	-23.58%	-1.76%	-1.90%	-2.45%	-2.94%
31/8/2011	0.05%	-10.46%	-22.83%	-18.52%	-6.78%	-7.31%	-7.93%	-7.71%
30/9/2011	0.03%	-4.87%	-22.18%	-12.12%	-3.16%	-3.40%	-4.27%	-3.76%
31/10/2011	0.03%	7.66%	14.03%	25.86%	4.99%	5.37%	5.69%	6.28%
30/11/2011	0.01%	-1.46%	-9.11%	17.81%	-0.95%	-1.02%	-1.40%	-0.06%
31/12/2011	0.01%	1.89%	-7.01%	0.00%	1.23%	1.33%	0.88%	1.23%
31/1/2012	0.02%	4.13%	25.38%	6.98%	2.69%	2.90%	3.96%	3.04%
29/2/2012	0.01%	3.91%	-6.13%	-3.26%	2.55%	2.74%	2.24%	2.38%
31/3/2012	0.01%	-0.43%	-8.50%	-4.49%	-0.28%	-0.30%	-0.70%	-0.50%
30/4/2012	0.01%	-2.18%	-4.07%	-18.82%	-1.41%	-1.52%	-1.62%	-2.36%
31/5/2012	0.01%	-6.90%	-25.28%	-8.70%	-4.48%	-4.83%	-5.75%	-4.92%
30/6/2012	0.01%	4.68%	-4.40%	3.17%	3.05%	3.28%	2.82%	3.20%
31/7/2012	0.00%	4.01%	16.76%	-3.08%	2.61%	2.81%	3.44%	2.45%
31/8/2012	0.00%	1.85%	5.99%	9.52%	1.20%	1.30%	1.50%	1.68%
30/9/2012	0.00%	0.92%	5.18%	2.90%	0.60%	0.64%	0.86%	0.74%
31/10/2012	0.00%	0.68%	5.64%	-7.04%	0.44%	0.48%	0.72%	0.09%
30/11/2012	0.00%	1.94%	-11.56%	-7.58%	1.26%	1.36%	0.68%	0.88%
31/12/2012	0.00%	1.54%	14.10%	-9.84%	1.00%	1.08%	1.71%	0.51%
31/1/2013	0.01%	2.72%	1.07%	7.27%	1.77%	1.91%	1.82%	2.13%
28/2/2013	0.00%	1.03%	-3.45%	-5.08%	0.67%	0.72%	0.50%	0.42%

31/3/2013	0.00%	1.25%	-8.25%	-7.14%	0.81%	0.87%	0.40%	0.46%
30/4/2013	0.00%	1.26%	-12.99%	1.92%	0.82%	0.88%	0.17%	0.92%
31/5/2013	0.00%	1.20%	11.46%	15.09%	0.78%	0.84%	1.35%	1.53%
30/6/2013	0.01%	-5.27%	-1.62%	-13.11%	-3.42%	-3.69%	-3.50%	-4.08%
31/7/2013	0.00%	5.11%	7.51%	7.55%	3.32%	3.58%	3.70%	3.70%
31/8/2013	0.01%	-0.68%	-2.79%	19.30%	-0.44%	-0.47%	-0.58%	0.53%
30/9/2013	0.00%	4.41%	11.67%	17.65%	2.87%	3.09%	3.45%	3.75%
31/10/2013	0.00%	3.83%	6.24%	5.00%	2.49%	2.68%	2.80%	2.74%
30/11/2013	0.01%	0.94%	2.71%	19.05%	0.61%	0.66%	0.75%	1.57%
31/12/2013	0.01%	1.03%	-8.44%	-6.00%	0.67%	0.72%	0.25%	0.37%
31/1/2014	0.01%	-1.60%	7.41%	5.32%	-1.04%	-1.12%	-0.67%	-0.77%
28/2/2014	0.01%	4.89%	3.32%	-20.20%	3.18%	3.43%	3.35%	2.17%
31/3/2014	0.01%	-1.05%	-1.10%	10.13%	-0.68%	-0.73%	-0.73%	-0.17%

Exhibit 2: OLS for Benchmark and 4 Portfolios

Benchmark

OLS Regression Results

Dep. Variable:	Benchmark	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	6.204e+32
Date:	Thu, 15 Nov 2018	Prob (F-statistic):	0.00
Time:	15:22:56	Log-Likelihood:	3727.9
No. Observations:	99	AIC:	-7452.
Df Residuals:	97	BIC:	-7447.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-1.084e-19	1.09e-18	-0.100	0.921	-2.27e-18	2.05e-18
TMI	0.6000	2.41e-17	2.49e+16	0.000	0.600	0.600

Omnibus:	10.627	Durbin-Watson:	1.688
Prob(Omnibus):	0.005	Jarque-Bera (JB):	25.327
Skew:	0.203	Prob(JB):	3.16e-06
Kurtosis:	5.444	Cond. No.	22.1

Portfolio 1

OLS Regression Results

Dep. Variable:	portfolio1	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	2.492e+33
Date:	Thu, 15 Nov 2018	Prob (F-statistic):	0.00
Time:	16:02:43	Log-Likelihood:	3788.8
No. Observations:	99	AIC:	-7574.
Df Residuals:	97	BIC:	-7569.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-8.132e-20	5.88e-19	-0.138	0.890	-1.25e-18	1.09e-18
TMI	0.6500	1.3e-17	4.99e+16	0.000	0.650	0.650

Omnibus:	38.965	Durbin-Watson:	1.632
Prob(Omnibus):	0.000	Jarque-Bera (JB):	138.716
Skew:	1.257	Prob(JB):	7.55e-31
Kurtosis:	8.226	Cond. No.	22.1

Portfolio 2

OLS Regression Results

Dep. Variable:	portfolio2	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	9.634e+32
Date:	Thu, 15 Nov 2018	Prob (F-statistic):	0.00
Time:	16:00:10	Log-Likelihood:	3734.5
No. Observations:	99	AIC:	-7465.
Df Residuals:	97	BIC:	-7460.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-1.084e-18	1.02e-18	-1.064	0.290	-3.11e-18	9.38e-19
TMI	0.7000	2.26e-17	3.1e+16	0.000	0.700	0.700
Omnibus:	35.284		Durbin-Watson:	1.366		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	70.491		
Skew:	-1.414		Prob(JB):	4.93e-16		
Kurtosis:	6.016		Cond. No.	22.1		

Portfolio 3

OLS Regression Results

Dep. Variable:	portfolio3	R-squared:	0.985
Model:	OLS	Adj. R-squared:	0.985
Method:	Least Squares	F-statistic:	6268.
Date:	Thu, 15 Nov 2018	Prob (F-statistic):	6.09e-90
Time:	16:01:02	Log-Likelihood:	403.08
No. Observations:	99	AIC:	-802.2
Df Residuals:	97	BIC:	-797.0
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.0004	0.000	0.902	0.369	-0.000	0.001
TMI	0.7344	0.009	79.171	0.000	0.716	0.753
Omnibus:	2.786		Durbin-Watson:	1.793		
Prob(Omnibus):	0.248		Jarque-Bera (JB):	2.188		
Skew:	0.337		Prob(JB):	0.335		
Kurtosis:	3.274		Cond. No.	22.1		

Portfolio 4

OLS Regression Results

```

=====
Dep. Variable:          portfolio4      R-squared:                0.955
Model:                  OLS             Adj. R-squared:           0.955
Method:                 Least Squares   F-statistic:              2064.
Date:                   Thu, 15 Nov 2018 Prob (F-statistic):       3.54e-67
Time:                   16:02:04         Log-Likelihood:           354.56
No. Observations:       99              AIC:                     -705.1
Df Residuals:           97              BIC:                     -699.9
Df Model:                1
Covariance Type:        nonrobust
=====

```

```

=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          -0.0009      0.001      -1.338      0.184      -0.002      0.000
TMI              0.6878      0.015      45.427      0.000      0.658      0.718
=====

```

```

=====
Omnibus:            12.884    Durbin-Watson:           2.244
Prob(Omnibus):      0.002    Jarque-Bera (JB):        40.358
Skew:                0.150    Prob(JB):                1.72e-09
Kurtosis:            6.113    Cond. No.                22.1
=====

```

Exhibit 3: OLS for Benchmark and 4 Portfolios
(without data in 2008)

Benchmark

OLS Regression Results

Dep. Variable:	Benchmark	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	1.568e+33
Date:	Fri, 16 Nov 2018	Prob (F-statistic):	0.00
Time:	10:46:27	Log-Likelihood:	3336.5
No. Observations:	87	AIC:	-6669.
Df Residuals:	85	BIC:	-6664.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-8.132e-20	5.9e-19	-0.138	0.891	-1.25e-18	1.09e-18
TMI	0.6000	1.52e-17	3.96e+16	0.000	0.600	0.600

Omnibus:	39.256	Durbin-Watson:	1.840
Prob(Omnibus):	0.000	Jarque-Bera (JB):	230.774
Skew:	-1.164	Prob(JB):	7.73e-51
Kurtosis:	10.632	Cond. No.	26.1

Portfolio 1

OLS Regression Results

Dep. Variable:	portfolio1	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	3.337e+05
Date:	Fri, 16 Nov 2018	Prob (F-statistic):	1.55e-154
Time:	10:44:42	Log-Likelihood:	557.61
No. Observations:	87	AIC:	-1111.
Df Residuals:	85	BIC:	-1106.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0003	4.39e-05	-7.970	0.000	-0.000	-0.000
TMI	0.6514	0.001	577.629	0.000	0.649	0.654

Omnibus:	15.566	Durbin-Watson:	0.083
Prob(Omnibus):	0.000	Jarque-Bera (JB):	15.373
Skew:	-0.959	Prob(JB):	0.000459
Kurtosis:	2.250	Cond. No.	26.1

Portfolio 2

OLS Regression Results

Dep. Variable:	portfolio2	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	5.262e+05
Date:	Fri, 16 Nov 2018	Prob (F-statistic):	6.07e-163
Time:	10:47:03	Log-Likelihood:	571.02
No. Observations:	87	AIC:	-1138.
Df Residuals:	85	BIC:	-1133.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0003	3.76e-05	-7.970	0.000	-0.000	-0.000
TMI	0.7012	0.001	725.426	0.000	0.699	0.703

Omnibus:	15.566	Durbin-Watson:	0.083
Prob(Omnibus):	0.000	Jarque-Bera (JB):	15.373
Skew:	-0.959	Prob(JB):	0.000459
Kurtosis:	2.250	Cond. No.	26.1

Portfolio 3

OLS Regression Results

Dep. Variable:	portfolio3	R-squared:	0.984
Model:	OLS	Adj. R-squared:	0.984
Method:	Least Squares	F-statistic:	5211.
Date:	Fri, 16 Nov 2018	Prob (F-statistic):	4.71e-78
Time:	10:47:38	Log-Likelihood:	365.57
No. Observations:	87	AIC:	-727.1
Df Residuals:	85	BIC:	-722.2
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0002	0.000	-0.444	0.658	-0.001	0.001
TMI	0.7401	0.010	72.184	0.000	0.720	0.760

Omnibus:	0.716	Durbin-Watson:	2.103
Prob(Omnibus):	0.699	Jarque-Bera (JB):	0.752
Skew:	0.208	Prob(JB):	0.687
Kurtosis:	2.815	Cond. No.	26.1

Portfolio 4

OLS Regression Results

Dep. Variable:	portfolio4	R-squared:	0.937
Model:	OLS	Adj. R-squared:	0.936
Method:	Least Squares	F-statistic:	1267.
Date:	Fri, 16 Nov 2018	Prob (F-statistic):	7.76e-53
Time:	10:48:43	Log-Likelihood:	308.11
No. Observations:	87	AIC:	-612.2
Df Residuals:	85	BIC:	-607.3
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0016	0.001	-2.086	0.040	-0.003	-7.53e-05
TMI	0.7063	0.020	35.589	0.000	0.667	0.746

Omnibus:	11.185	Durbin-Watson:	2.292
Prob(Omnibus):	0.004	Jarque-Bera (JB):	29.423
Skew:	0.195	Prob(JB):	4.08e-07
Kurtosis:	5.822	Cond. No.	26.1

Python Code

```
Title: Investment Case II
# Author: Yang Chenyu
# Number: 2016301550186
# Date: 11/13/2018
# I save the data I need as .csv in the Pycharm environment
# All path is the project itself

# import all the modules that I need
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm

# Question 1-----

TMI = pd.read_csv('STOXX_TMI.csv').sort_index(ascending=False)
TKA = pd.read_csv('TKA.csv').sort_index(ascending=False)
OLE = pd.read_csv('OLE.csv').sort_index(ascending=False)

# Transfer the str into float
TMI['Return'] = TMI['Return'].str.strip('%').astype(float) / 100
TKA['Return'] = TKA['Return'].str.strip('%').astype(float) / 100
OLE['Return'] = OLE['Return'].str.strip('%').astype(float) / 100

# Calculate the risk of these three assets
TMI_risk = TMI['Return'].std()
TKA_risk = TKA['Return'].std()
OLE_risk = OLE['Return'].std()

# Question 3-----

portion1 = np.array([0.35, 0.65]) # risk-free, index
portion2 = np.array([0.3, 0.7]) # risk-free, index
portion3 = np.array([0.3, 0.65, 0.05]) # risk-free, index, TKA
portion4 = np.array([0.3, 0.65, 0.05]) # risk-free, index, OLE

bond = pd.read_csv('German T-
Bills.csv').sort_index(ascending=False)
bond['Return'] = bond['Return'].str.strip('%').astype(float) /
100
data = bond

# Merge different DataFrames to get a total data set of returns
for i in ['TMI', 'TKA', 'OLE']:
    data = pd.merge(data, eval(i).iloc[:, [0, 2]], on='Date',
how='outer')
data.columns = ['Date', 'Bond', 'TMI', 'TKA', 'OLE']
```

```

# Add the returns of different portfolios into the DataFrame
data['portfolio1'] = (data.iloc[:, [1, 2]] *
portion1).sum(axis=1)
data['portfolio2'] = (data.iloc[:, [1, 2]] *
portion2).sum(axis=1)
data['portfolio3'] = (data.iloc[:, [1, 2, 3]] *
portion3).sum(axis=1)
data['portfolio4'] = (data.iloc[:, [1, 2, 4]] *
portion4).sum(axis=1)

# save this data for Problem 7
data_dat = data.copy()

# Calculate the risk of the 4 portfolios
port1_risk = data['portfolio1'].std()
port2_risk = data['portfolio2'].std()
port3_risk = data['portfolio3'].std()
port4_risk = data['portfolio4'].std()

# Because the result is different from my prediction, I chose to
calculate the correlations
data.iloc[:, 1:5].corr().to_csv('correlation.csv')

# Question 4-----

# The data for this problem is this
data = data.iloc[:, :5]

# Get the excess return
for i in range(2, 5):
    data.iloc[:, i] = data.iloc[:, i] - data.iloc[:, 1]
data = data.iloc[:, [0, 2, 3, 4]]

# Regression for TKA
Y_TKA = data.iloc[:, 2]
X_TKA = data.iloc[:, 1]
X_TKA = sm.add_constant(X_TKA)

# Use statsmodels to do the OLS rather than sklearn
model = sm.OLS(Y_TKA, X_TKA)
results = model.fit()
alpha, beta = results.params
x_fit = np.array(X_TKA)
y_fit = results.fittedvalues

# Calculate the total risk, system risk and nonmarket risk
total_risk_TKA = data.iloc[:, 2].std()
sys_risk_TKA = beta * data.iloc[:, 1].std()
nonsys_risk_TKA = (results.fittedvalues - Y_TKA).std()

# Plot for TKA

```

```

plt.scatter(data.iloc[:, 1], data.iloc[:, 2], c='r',
            label='Actual')
plt.plot(x_fit[:, 1], y_fit, label='OLS', linewidth=2, c='b')
plt.xlabel('TMI')
plt.ylabel('TKA')
plt.title('Single-Index Model for TKA')
plt.xlim(-0.15, 0.15)
plt.ylim(-0.4, 0.3)
plt.grid()
plt.legend()
plt.show()

# Regression for OLE
Y_OLE = data.iloc[:, 3]
X_OLE = data.iloc[:, 1]
X_OLE = sm.add_constant(X_OLE)
model = sm.OLS(Y_OLE, X_OLE)
results = model.fit()
alpha, beta = results.params
x_fit = np.array(X_OLE)
y_fit = results.fittedvalues

# Calculate the total risk, system risk and nonmarket risk
total_risk_OLE = data.iloc[:, 3].std()
sys_risk_OLE = beta * data.iloc[:, 1].std()
nonsys_risk_OLE = (results.fittedvalues - Y_OLE).std()

# Plot for OLE
plt.scatter(data.iloc[:, 1], data.iloc[:, 3], c='r',
            label='Actual')
plt.plot(x_fit[:, 1], y_fit, label='OLS', linewidth=2, c='b')
plt.xlabel('TMI')
plt.ylabel('OLE')
plt.title('Single-Index Model for OLE')
plt.grid()
plt.xlim(-0.15, 0.15)
plt.ylim(-0.6, 0.6)
plt.legend()
plt.show()

# Question 7-----

# deep copy in order to get original data
data = data_dat.copy()

# Generate Benchmark 40% bonds & 60% market index
benchmark = data.iloc[:, :3]
benchmark['Benchmark'] = (data.iloc[:, [1, 2]] * np.array([0.4,
0.6])).sum(axis=1) - benchmark['Bond']
benchmark['TMI'] = benchmark['TMI'] - benchmark['Bond']
benchmark = benchmark.iloc[:, [0, 2, 3]]

```

```

# OLS for benchmark
X_benchmark = benchmark.iloc[:, 1]
X_benchmark = sm.add_constant(X_benchmark)
Y_benchmark = benchmark.iloc[:, 2]
results = sm.OLS(Y_benchmark, X_benchmark).fit()
alpha_bench, beta_bench = results.params

# Calculate the total risk, system risk and nonmarket risk
total_risk_benchmark = benchmark.iloc[:, 2].std()
sys_risk_benchmark = beta_bench * benchmark.iloc[:, 1].std()
nonsys_risk_benchmark = (results.fittedvalues -
Y_benchmark).std()

# Generate the excess return of portfolios
data.iloc[:, 2] = data.iloc[:, 2] - data.iloc[:, 1]
for i in range(5, 9):
    data.iloc[:, i] = data.iloc[:, i] - data.iloc[:, 1]
data = data.iloc[:, [0, 2, 5, 6, 7, 8]]

# Portfolio 1
Y_p1 = data.iloc[:, 2]
X_p1 = data.iloc[:, 1]
X_p1 = sm.add_constant(X_p1)
model = sm.OLS(Y_p1, X_p1)
results = model.fit()
alpha_p1, beta_p1 = results.params

# Calculate the total risk, system risk and nonmarket risk
total_risk_p1 = data.iloc[:, 2].std()
sys_risk_p1 = beta_p1 * data.iloc[:, 1].std()
nonsys_risk_p1 = (results.fittedvalues - Y_p1).std()

# Portfolio 2
Y_p2 = data.iloc[:, 3]
X_p2 = data.iloc[:, 1]
X_p2 = sm.add_constant(X_p2)
model = sm.OLS(Y_p2, X_p2)
results = model.fit()
alpha_p2, beta_p2 = results.params

# Calculate the total risk, system risk and nonmarket risk
total_risk_p2 = data.iloc[:, 3].std()
sys_risk_p2 = beta_p2 * data.iloc[:, 1].std()
nonsys_risk_p2 = (results.fittedvalues - Y_p2).std()

# Portfolio 3
Y_p3 = data.iloc[:, 4]
X_p3 = data.iloc[:, 1]
X_p3 = sm.add_constant(X_p3)
model = sm.OLS(Y_p3, X_p3)
results = model.fit()
alpha_p3, beta_p3 = results.params

```

```

# Calculate the total risk, system risk and nonmarket risk
total_risk_p3 = data.iloc[:, 4].std()
sys_risk_p3 = beta_p3 * data.iloc[:, 1].std()
nonsys_risk_p3 = (results.fittedvalues - Y_p3).std()

# Portfolio 4
Y_p4 = data.iloc[:, 5]
X_p4 = data.iloc[:, 1]
X_p4 = sm.add_constant(X_p4)
model = sm.OLS(Y_p4, X_p4)
results = model.fit()
alpha_p4, beta_p4 = results.params

# Calculate the total risk, system risk and nonmarket risk
total_risk_p4 = data.iloc[:, 5].std()
sys_risk_p4 = beta_p4 * data.iloc[:, 1].std()
nonsys_risk_p4 = (results.fittedvalues - Y_p4).std()

# Problem 9

data = data_dat.copy()
# Remove the data of 2018
data = data[data['Date'].apply(lambda x: False if
x.__contains__('2008') else True)]

# Generate Benchmark 40% bonds & 60% market index
benchmark = data.iloc[:, :3]
benchmark['Benchmark'] = (data.iloc[:, [1, 2]] * np.array([0.4,
0.6])).sum(axis=1) - benchmark['Bond']
benchmark['TMI'] = benchmark['TMI'] - benchmark['Bond']
benchmark = benchmark.iloc[:, [0, 2, 3]]

# OLS for benchmark
X_benchmark = benchmark.iloc[:, 1]
X_benchmark = sm.add_constant(X_benchmark)
Y_benchmark = benchmark.iloc[:, 2]
results = sm.OLS(Y_benchmark, X_benchmark).fit()
alpha_bench, beta_bench = results.params

# Calculate the total risk, system risk and nonmarket risk
total_risk_benchmark = benchmark.iloc[:, 2].std()
sys_risk_benchmark = beta_bench * benchmark.iloc[:, 1].std()
nonsys_risk_benchmark = (results.fittedvalues -
Y_benchmark).std()

# Generate the excess return of portfolios
data.iloc[:, 2] = data.iloc[:, 2] - data.iloc[:, 1]
for i in range(5, 9):
    data.iloc[:, i] = data.iloc[:, i] - data.iloc[:, 1]
data = data.iloc[:, [0, 2, 5, 6, 7, 8]]

```

```

# Portfolio 1
Y_p1 = data.iloc[:, 2]
X_p1 = data.iloc[:, 1]
X_p1 = sm.add_constant(X_p1)
model = sm.OLS(Y_p1, X_p1)
results = model.fit()
alpha_p1, beta_p1 = results.params

# Calculate the total risk, system risk and nonmarket risk
total_risk_p1 = data.iloc[:, 2].std()
sys_risk_p1 = beta_p1 * data.iloc[:, 1].std()
nonsys_risk_p1 = (results.fittedvalues - Y_p1).std()

# Portfolio 2
Y_p2 = data.iloc[:, 3]
X_p2 = data.iloc[:, 1]
X_p2 = sm.add_constant(X_p2)
model = sm.OLS(Y_p2, X_p2)
results = model.fit()
alpha_p2, beta_p2 = results.params

# Calculate the total risk, system risk and nonmarket risk
total_risk_p2 = data.iloc[:, 3].std()
sys_risk_p2 = beta_p2 * data.iloc[:, 1].std()
nonsys_risk_p2 = (results.fittedvalues - Y_p2).std()

# Portfolio 3
Y_p3 = data.iloc[:, 4]
X_p3 = data.iloc[:, 1]
X_p3 = sm.add_constant(X_p3)
model = sm.OLS(Y_p3, X_p3)
results = model.fit()
alpha_p3, beta_p3 = results.params

# Calculate the total risk, system risk and nonmarket risk
total_risk_p3 = data.iloc[:, 4].std()
sys_risk_p3 = beta_p3 * data.iloc[:, 1].std()
nonsys_risk_p3 = (results.fittedvalues - Y_p3).std()

# Portfolio 4
Y_p4 = data.iloc[:, 5]
X_p4 = data.iloc[:, 1]
X_p4 = sm.add_constant(X_p4)
model = sm.OLS(Y_p4, X_p4)
results = model.fit()
alpha_p4, beta_p4 = results.params

# Calculate the total risk, system risk and nonmarket risk
total_risk_p4 = data.iloc[:, 5].std()
sys_risk_p4 = beta_p4 * data.iloc[:, 1].std()
nonsys_risk_p4 = (results.fittedvalues - Y_p4).std()

```